Multi-Step Neutrosophic Cognitive Map Based Decision Making Framework for Short-Term Financial Stock Market Price Trend Prediction

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Abstract

Neutrosophic cognitive maps are expansion of fuzzy cognitive maps, containing indetermination in causal relations. Fuzzy cognitive maps do not require an indeterminate relationship, making it less adequate for real-time applications. A logic in which every proposition is projected to have the truth percentage in subset T and the falsity percentage in subset F is named Neutrosophic Logic. This logic is also considered the general form of Intuitionistic fuzzy logic. Stock price prediction is a main topic in economics and finance, which has promoted the priority of investigators in recent years to improve improved predictive methods. Predicting price and tendency of the stock market denote indispensable features of finance and investment. Many scientists have presented their ideas to predict the market price to make money while trading utilizing different methods like statistical and technical analysis. This manuscript proposes a Neutrosophic Cognitive Map-Based Short-Term Financial Stock Market Price Trend Prediction (NCM-SFSMPTP) model. The main goal of NCM-SFSMPTP technique relies on improving the accurate approach for stock market price trend prediction. At first, the min-max normalization methodology is utilized in the data normalization phase to standardize and scale data for consistency, comparability, and efficient processing. For the classification process, the neutrosophic cognitive map (NCM) technique is employed. Finally, the improved arithmetic optimization algorithm (IAOA)-based hyper-parameter selection is implemented to enhance the classification outcomes of the NCM system. The performance validation of the NCM-SFSMPTP methodology is verified under the Apple Stock Price Trend and Indicators dataset and the outcomes are determined regarding to several measures. The experimental validation of the NCM-SFSMPTP method illustrated a superior accuracy value of 94.79% over existing models in stock market price trend prediction process.

Keywords: Neutrosophic Cognitive Map; Fuzzy Logic; Neutrosophic Set; Financial Stock Market Price Trend Prediction; Improved Arithmetic Optimization Algorithm

1. Introduction

Neutrosophic logic is the field of neonate analysis in which every proposition is measured to have the proportions of indeterminacy in subset I, falsity in subset F, and truth in subset T [1]. A neutrosophic set (NS) is effectively implemented for unknown data processing and offers advantages to overcome the indeterminacy data and a model supported for classification and data analysis applications [2]. NS delivers an accurate and efficient methodology to explain imbalanced data depending upon the data features. Stock is an economic product identified by flexible

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trading, higher risk and return that are preferred by multiple investors [3]. Nevertheless, various aspects like market condition, macroeconomic situation, major economic and social events, managerial decisions, companies and investor's preferences [4] determine the stock price. SPP (SPP) has attention and complicated investigation concept. Econometric and statistical methods are widely employed in conventional SPP, but these models cannot handle the complex and dynamic setting of stock market [5]. With the faster growth of computer technology, scholars have begun utilizing machine learning (ML) for forecasting fluctuations and stock prices, assisting investors regulate investment approaches to diminish risk and rise returns [6].

The stock market is an extremely complicated time-series and has distinctive dynamic features. In addition, multiple unpredictable aspects that leads to distinctive non-stationary stock price time-series data [7] influence the stock price. SPP is the more significant concept in business and finance. Nevertheless, the stock market field is unpredictable and dynamic [8]. Many investigatory works have been implemented for forecasting the market to make benefits utilizing diverse models ranging between technical, and statistical analysis, to fundamental analysis between others, with diverse outcomes. These models cannot offer deeper analysis that is needed and ineffectual to forecast stock market prices [9]. Thus, in recent years various techniques and models have advanced to SPP. Owing to its inherent ambiguity, the task of predicting economic time series is challenging, here conventional statistical methods like ML models and artificial neural networks (ANN) have been extensively inspected. ML has been generally employed to SPP recently and more appropriate methods for stock prediction has been projected [10]. Numerous surveys exposed that deep learning (DL) has higher efficacy than traditional methodologies.

This manuscript proposes a Neutrosophic Cognitive Map-Based Short-Term Financial Stock Market Price Trend Prediction (NCM-SFSMPTP) model. The main goal of NCM-SFSMPTP technique relies on improving the accurate approach for stock market price trend prediction. At first, the min-max normalization methodology is utilized in the data normalization phase to standardize and scale data for consistency, comparability, and efficient processing. For the classification process, the neutrosophic cognitive map (NCM) technique is employed. Finally, the improved arithmetic optimization algorithm (IAOA)-based hyper-parameter selection is implemented to enhance the classification outcomes of the NCM system. The performance validation of the NCM-SFSMPTP methodology is verified under the Apple Stock Price Trend and Indicators dataset and the outcomes are determined regarding to several measures. The key contribution of the NCM-SFSMPTP methodology is listed below.

- The NCM-SFSMPTP model standardizes input data through min-max normalization, bringing all values into a consistent range. This preprocessing step ensures that the classifier can efficiently process the data without being influenced by varying scales. As a result, the overall performance and accuracy of the model are improved.
- The NCM-SFSMPTP method utilizes the NCM method for classification, to manage uncertainty and imprecision in data. This approach improves decision-making processes, allowing for predictions that are more robust. As a result, classification accuracy is significantly improved, particularly in complex and uncertain scenarios.
- The NCM-SFSMPTP technique employs the IAOA approach to fine-tune its hyperparameters, improving prediction precision. This optimization process confirms that the model operates at peak efficiency, mitigating computational complexity. As a result, the overall accuracy and performance of the model are significantly improved.
- The novelty of the NCM-SFSMPTP model is in incorporating NCM with the IAOA method. This integration enables the model to effectually handle uncertainty in complex decision-making scenarios. Additionally, the use of IAOA allows for precise hyperparameter tuning, improving the predictive performance and robustness of the technique.

2. Literature Survey

Dhanalakshmi et al. [11] combine the MCDM model to establish the optimum stocks for investment. The Analytic Hierarchy Process (AHP) is employed to assign weights to multiple economic factors. Stock analysis comprises various sub- and criteria that can result in an inappropriate answer. Peivandizadeh et al. [12] develop a novel method which controls the ability of sentiment analysis (SA) incorporated with stock market data for SPP. The Off-policy Proximal Policy Optimizer (PPO) model, particularly intended for managing class inequality by fine-tuning the reward mechanism in the training stage, consequently supporting the precise classification of smaller class samples. A further obstacle is effectually incorporating the temporal dynamics of stock prices with SA outcomes. This solution was applying a Transductive Long Short-Term Memory (TLSTM) method, which combines SA results with historic stock data. In [13], a DL model is intended for the stock market tendency prediction. Initially, stock market data is derived from benchmark resources and delivered to the time-series data formation stage. Deep convolutional temporal network (DCTN) is employed here. Afterward, the obtained aspects are offered to the phase of prediction, and effectual prediction is developed by employing adaptive dual attention-based LSTM (ADA-LSTM). Moreover, their parameters are adjusted with the assistance of hybrid fruit fly spider

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monkey optimizer (HFF-SMO) by combining fruit fly algorithm (FFO) and spider monkey algorithm (SMO) to obtain an efficient rate of stock market prediction.

In [14], an innovative method to forecast stock market prices is presented, such as stock market prediction depending on DL (SMP-DL). The projected model partitions into dual phases (I) SPP and (II) data pre-processing (DP). During the primary level, data is pre-processed for attaining cleaned ones over multiple phases, which is reject, detect missing values, data normalization, and feature selection. During SPP, LSTM integrated with the bi-directional gated recurrent unit (Bi-GRU) for predicting the closing price of stock market. Amiri et al. [15] presents a hybrid method that combines a GCN with an attention-enhanced LSTM structure. By utilizing a graph framework originated from DTW, the GCN acquires inter-stock relations, whereas the attention mechanism inside the LSTM enhances the temporal dynamic modelling, permitting the method aimed at the more significant historic data. Huang et al. [16] developed an innovative method to improve investment returns by combining LSTM predictions with the evolutionary operating-weights (EOW) approach. The projected model utilizes a multi-layer LSTM to predict upcoming stock prices, integrating the predictions with real-time marketing data and originating an operational approach utilizing EOW model.

A. Limitations and Research Gap

Despite the improvements in stock market prediction methods, various limitations remain. Many models, such as those using SA or DL, face difficulty with integrating the full complexity of market dynamics, particularly temporal factors and class imbalance. The reliance on historical data often overlooks real-time market conditions, restricting the adaptability of these models. Furthermore, while hybrid approaches, like integrating LSTM with other optimization techniques, improve accuracy, they can introduce significant computational complexity and may not scale well with massive datasets. Privacy concerns related to the use of market data are also often overlooked. Moreover, the diversity of models across diverse industries and financial contexts suggests a need for more generalized solutions that can adapt to different market conditions and datasets. Further research is required to address these gaps, specifically in real-time prediction and more efficient handling of large-scale data.

3. The Proposed Method

In this work, a novel NCM-SFSMPTP model is proposed. The main goal of NCM-SFSMPTP model relies on improving the accurate approach for stock market price trend prediction. Fig. 1 signifies the workflow of the NCM-SFSMPTP approach.

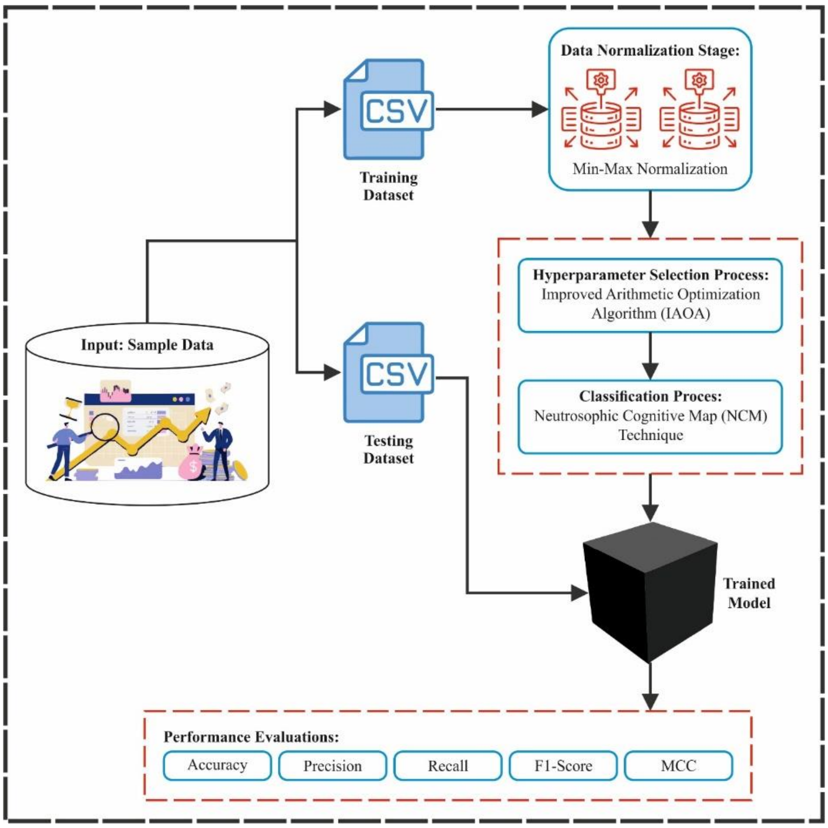

Figure 1. Workflow of NCM-SFSMPTP model

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A. Stage I: Predictor Selection

At first, the min-max normalization methodology is used in the data normalization phase to standardize and scale data for consistency [17]. This is a widely used technique for rescaling data to a specific range, typically between 0 and 1. The key merit of choosing this technique is its simplicity and efficiency in handling features with varying scales, ensuring that no single feature dominates the learning process due to its larger range. Unlike Z-score normalization, which is sensitive to outliers, min-max normalization retains the original distribution of the data without assuming a normal distribution. It is specifically useful when the model requires features to have a bounded range, such as in neural networks, where activation functions like sigmoid or tanh perform better with scaled inputs. Furthermore, this technique can assist in improving the convergence rate of many ML models by providing a uniform scale, making it ideal for optimization tasks.

Min-Max Normalization is a feature scaling approach applied in stock market price prediction to convert stock prices into the predefined interval, normally [0,1] or [-1,1]. This guarantees that each value is uniformly scaled without changing their relationships. It assists in decreasing the influence of greatest price variations, making methods more efficient and stable. By maintaining the new distribution, this model improves pattern recognition in ML techniques. It is mainly valuable for regression models and neural networks, guaranteeing that great stock price values do not control smaller ones. It is important in financial processing of data, whereas dissimilar stock prices have varied scales. Followed by, NCM based prediction approach is applied and its performance is boosted by parameter optimizer.

B. Stage I: Predictor Selection

For the classification process, the NCM technique is employed. This is a powerful technique for handling uncertainty, vagueness, and imprecision in decision-making. The key merit of utilizing NCM is its capability to model intrinsic associations and interdependencies among variables, allowing for more accurate and flexible classification in scenarios with incomplete or uncertain data. Unlike conventional methods, NCM integrates a degree of truth, indeterminacy, and falsity, enabling the model to better represent real-world complexity. This approach is specifically useful when dealing with ambiguous or contradictory information, as it gives a more complex understanding of data. Furthermore, NCM-based classification can adapt to dynamic systems, making it appropriate for applications like financial prediction or medical diagnoses, where conditions frequently change. Its capability to handle uncertain data gives it a distinct advantage over deterministic models.

Definition1: Assume X remain discourse universe [18]. An NS was described by 3 membership functions (MFs), $u_A(x), r_A(x), v_A(x){:}X \to]^-0,1^+[$ that fulfill the state $-0 \leq \inf u_A(x) + inf r_A(x) + \inf v_A(x) \leq \sup u_A(x) + \sup r_A(x) + sup\ v_A(x) \leq 3^+$ for each $x \in X$. $u_A(x), r_A(x)$ and $V_A(x)$ denote MFs of falseness, indeterminacy and truthfulness of x in A, individually.

Definition2: ([1, 2, 3]) Assume X remain discourse universe. A single-valued NS (SVNS) A on denote collection by type:

$$A = \{\langle x, u_A(x), r_A(x), v_A(x)\rangle : x \in X\} \tag{1}$$

Whereas $u_A, r_A, v_A{:}X \to [0,1]$, fulfill the state $0 \leq u_A(x) + r_A(x) + v_A(x) \leq 3$ for every $x \in X$. $u_A(x), r_A(x)$ and $v_A(x)$ symbolize the MFs of falseness, indeterminate, and truthfulness of x in A, correspondingly. For ease of use, a SVNN should be demonstrated as $A = (a, b, c)$, whereas $a, b, c \in [0,1]$ and fulfill $0 \leq a + b + c \leq 3$.

Other main descriptions are associated with the graphs.

Definition3: dotted lines characterize Neutrosophic graph is a graph comprising any of them indeterminate edge that.

Definition4: A neutrosophic directed graph (NDG) represents directed graph encompassing one or more indeterminate edge that is characterized by dotted lines.

Definition5: A NCM is an NDG of which nodes symbolize ideas and whose edges denote causal relationships between the edges.

When $C_1, C_2, \dots, C_k$ are k nodes, all of the $C_i (i = 1,2, \dots, k)$ is symbolized by the vector $(x_1, x_2, \dots, x_k)$ whereas $x_i \in \{0,1,I\}$. $x_i = 0$ implies that the node C_i lies within the activated condition, $x_i = 1$ indicates that the node C_i lies within the deactivated condition and $x_i =$ I that denote the node C_i is encompassed by the indeterminate condition, in a particular situation or time.

When C_m and C_n denote dual nodes, an edge-controlled form C_m to C_n is named links and characterizes the causality from C_m to C_n. All nodes is related to a weight inside the set $\{-1,0,1,I\}$. When α_{mn} represents the edge weight $C_m C_n$, $\alpha_{mn} \in \{-1,0,1,I\}$:

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$\alpha_{mn} = 0$ when C_m doesn't affect C_n,

$\alpha_{mn} = 1$ when a growth (decline) in C_m gives a rise (decrease) in C_n,

$\alpha_{mn} = -1$ when a growth (decline) in C_m gives a decrease (rise) in C_n,

$\alpha_{mn} = I$ when the result of C_m on C_n is indeterminate.

Definition6: An NCM has edges with weights in $\{-1,0,1,I\}$ is named the simple NCM.

Definition7: When $C_1, C_2, \dots, C_k$ represents nodes. The neutrosophic matrix $N(E)$ is described as $(E) = (\alpha_{mn})$, while α_{mn} represents the weighting of the focused edge C_mC_n, so that $\alpha_{mn} \in \{-1,0,1,I\}$. $N(E)$ is named the neutrosophic adjacency matrix.

Definition8: Assume $C_1, C_2, \dots, C_k$ remain nodes. Assume $A = (a_1, a_2, \dots, a_k)$, whereas $a_m \in \{-1,0,1,I\}$.

Definition9: Assume $C_1, C_2, \dots, C_k$ remain nodes. Suppose $\overrightarrow{C_1C_2}$, $\overrightarrow{C_2C_3}$, $\overrightarrow{C_3C_4}\dots$,$\overrightarrow{C_mC_n}$ exist edges, formerly the edges organize managed cycles.

Definition10: An NCM comprising cycles considered to have a response. After there is response in the NCM, it has been said that it is a dynamical system.

Definition11: Assume $\overrightarrow{C_1C_2}$, $\overrightarrow{C_2C_3}$, $\overrightarrow{C_3C_4}$,…,$\overrightarrow{C_{k-1}C_k}$ exists cycle. If C_m is activated and its causality passes over the cycle edges and then it constitutes reason C_m itself, formerly the dynamical method distributes.

Definition12: When the equilibrium states of the dynamical system are an only states, then it was named static points. An instance of a fixed point is after dynamical models begin by be activated by C_1. When it is presumed that the NCM occupiesC_1 and C_k, for example: the state to be $(1,0,\dots,0,1)$, so these vectors of the NS are named a fixed point.

Definition13: When the NCM is determined using NS-vectors, which reiterations itself in the pattern: $A_1 \rightarrow A_2 \rightarrow \dots \rightarrow A_m \rightarrow A_1$, then the equilibrium is named a limited cycle.

Model to determine the Hidden Patterns

Assume $C_1, C_2, \dots, C_k$ exist as nodes with feedback. Suppose that E denote the related adjacency matrix. A hidden form is discovered after C_1 is activated and an input vector $A_1 = (1,0,\dots,0,1)$ is provided. The data should pass over the $N(E)$ that is gained by multiplying A_1 by the matrix $N(E)$.

Assume $A_1N(E) = (\alpha_1, \alpha_2, \dots, \alpha_k)$ by the threshold process of substituting α_m by 1 when $\alpha_m > p$ and α_m by 0 when $\alpha_m < p$ (p denote proper positive number) and α_m is substituted by I when this cannot be a number. The resultant notion is upgraded; vector C_1 is involved in the upgraded vector by converting the initial coordination of the resultant vector into 1.

When $A_1N(E) \rightarrow A_2$ was presumed then $A_2N(E)$ is measured and the similar process is reiterated. This process is reiterated till a fixed point or border cycle has been attained.

Definition14: A neutrosophic number N was described as a number as shown:

$$N = d + I \tag{2}$$

Whereas d and I is named the determinate and indeterminate portions.

Provided that $N_1 = a_1 + b_1$ I and $N_2 = a_2 + b_2$ I denote dual neutrosophic numbers, and similar processes between them are delineated as demonstrated:

$$N_1 + N_2 = a_1 + a_1 + (b_1 + b_2)I\ (Addition);$$

$$N_1 - N_2 = a_1 - a_1 + (b_1 - b_2)I\ (Subraction),$$

$$N_1 \times N_2 = a_1a_2 + (a_1b_2 + b_1a_2 + b_1b_2)I\ (Multiplication),$$

$$\frac{N_1}{N_2} = \frac{a_1 + b_1I}{a_2 + b_2I} = \frac{a_1}{a_2} + \frac{a_2b_1 - a_1b_2}{a_2(a_2 + b_2)}I\ (Division).$$

C. Stage II: Parameter Selection

Eventually, the IAOA-based hyper-parameter selection process is implemented to enhance the classification outcomes of NCM [19]. This selection process presents significant merits in optimizing ML methods. One key merit is its capability to effectually explore the solution space, finding optimal hyper-parameters while minimizing computational cost. IAOA enhances upon conventional optimization techniques by utilizing a population-based

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approach, which allows for a broader search and better handling of complex, multi-dimensional hyper-parameter spaces. This methodology also provides faster convergence compared to gradient-based approaches, making it ideal for models with non-differentiable or noisy objective functions. Moreover, IAOA is less likely to be stuck in local minima, ensuring more robust optimization. The simplicity and flexibility of the algorithm makes it appropriate for various types of ML models, offering a significant advantage in hyper-parameter tuning over more conventional techniques like grid or random search.

The basis for elementary mathematical operations, like subtraction, addition, division, and multiplication act as the foundation for the AOA, which is a device to solve mathematical problems. The AOA follows the normal population-based algorithmic optimizer process that contains the exploitation and exploration stages. However, exploitation focuses on increasing the precision of the solution, exploration tries to comprehensively exploring the searching area.

Initialization

The initial phase in the optimizer procedure of AOA includes generating a collection of possible solutions (mentioned as X) by possibility. Every consecutive iteration leads to that single candidate solution that is anticipated to be both the optimal solution or at least the nearer to it inside a neighborhood.

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{N,1} & \cdots & x_{N,n} & \cdots & x_{N,n} \end{bmatrix} \tag{3}$$

It is essential to select prior to start the process of AOA, should commence with both the exploitation or exploration stages. The functional value at the l^{th} iteration measured by utilizing the Math Optimizer Accelerated (MOA) function that is described by Eq. (4).

$$MOA\ (C_{lt}) = \text{Min} + C_{lt} \times \left(\frac{\text{Max} - \text{Min}}{M_{It}}\right) \tag{4}$$

M_{It} signifies the maximal repetition counts. Based on the accelerated function, Max and Min characterize their lowest and highest values, correspondingly.

Exploration

During this exploration stage, Multiplication (MO) or Division (DO) operators is utilized, however these movements probably might not approach the objective competently and can simply converge near a near-optimal solution after various series. Eq. (5) offers equations to update locations and summarize the two major searching strategies utilized in exploration.

$$x'_{i,j} = \begin{cases} x_{b,j} \div (MOP + \varepsilon) \times \left(\left(ub_j - lb_j\right) \times \mu + lb_j\right), \\ r_2 < 0.5 \\ x_{b,j} \times MOP \times \left(\left(ub_j - lb_j\right) \times \mu + lb_j\right), \\ otherwise \end{cases} \tag{5}$$

It provides a direct model of making adjacent solutions. Now, $x_{\mathrm{i,j}}$ refers to location at the j^{th} position of the currently optimal-acquired solution, $x'_{\mathrm{i,j}}$ denote location at the j^{th} location of the l^{th} solution, ε represent a smaller integer, and μ means controller parameters. MOP (C) is specified as shown:

$$MOP\ (C_{lt}) = 1 - \left(\frac{C_{It}}{M_{It}}\right)^{\frac{1}{\alpha}} \tag{6}$$

In following iterations of the exploitation procedure, the accuracy achieved is measured by main parameters, characterized by α.

Exploitation

The mathematical calculations utilize operators like Addition (AO) and Subtraction (SO) and, to make outcomes of target results in the exploitation stage. Over many iterations, these operators permit for effective targeting of the expected outcome. The key searching strategies and location-updated equations for the phase are provided in Eq. (7). In the meantime, the exploitation operators (AO and SO), assistance the performance in discovering the optimal solutions inside associated searching models such that the method may not be stuck into the local searching region.

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$$x'_{i,j} = \begin{cases} x_{b,j} - MOP \times \left(\left(ub_j - lb_j \right) \times \mu + lb_j \right), r_3 > 0.5 \\ x_{b,j} + MOP \times \left(\left(ub_j - lb_j \right) \times \mu + lb_j \right), otherwise \end{cases} \quad (7)$$

An arbitrary quantity that is consistently divided through (0, 1) is represented by r_3.

A widely known problem of the original AOA early converging to unsatisfactory solutions. Regardless, the AOA is even beneficial to examine searching regions. The IAOA differentiates among the exploitation and exploration phases, every subject to various regulations concerning location upgrades, by comparison with the original AOA. For instance, originated by Eq. (5), in AOA, in the exploration stage, most of the efforts will concentration on the well-known solution, which leads to faster decline of population diversity at the initial phases of the searching procedure. Larger solution stages might spread away from the search area outcome from too traditional limitations. Nevertheless, moderate stages made by neighbouring constraints increase the probability of premature convergence to poor solutions.

Similar adjustments are produced to all features of the optimal solution, which has been establish in every iteration, when $r_2 > 0.5$, as presented by Eq. (6) $(MOP + \varepsilon) \times \left(\left(ub_j - lbj \right) \times \mu + lb_j \right)$. Correspondingly, in the optimal solution discovered till now, every design variable was scaled through the identical factor $\times \left(\left(ub_j - lb_j \right) \times \mu + lb_j \right)$. It is very common that due to the limited range, unsatisfactory solutions converge gradually and early. IAOA has presented a novel location-updated method. Which utilizes multiplication and division operations to deal with these issues in the exploration stage of the original AOA.

$$x'_{i,j} = \begin{cases} x_{i,j} \div (1 + \left(-1 \right)^{rand_i([1,2])}) \, 0.5 \times rand \times \overline{MOP}, \\ r_2 > 0.5 \\ x_{i,j} \times (1 + \left(-1 \right)^{rand_j([1,2])}) \, 0.5 \times rand \times \overline{MOP}, \\ otherwise \end{cases} \quad (8)$$

A pseudo-random number in (0,1) by a uniform distribution is characterized by $rand$. For the l^{th} candidate solution, the current value of the j^{th} design variable is represented by $x'_{i,j}$. The parameter-free form of the MOP function, signified by $\overline{MOP}$, is described as demonstrated: The function of MOP has a difference named $\overline{MOP}$, which works without the requirement for some additional parameters.

$$\overline{MOP}(C_{It}) = \left(1 - \frac{C_{lt}}{M_{lt}} \right)^{rand_i([1,2])} \quad (9)$$

By comparison with the original AOA, during this IAOA exploration stage, as characterized by Eq. (5), it underlines the current location of the solutions. This permits complete exploration of the searching region and prevents diversity loss in the search processes. Moreover, utilizing randomly generated numbers in Eqs. (8) and (9) outcomes in the group of different step sizes. The convergence-related difficulties can lower as Eq. (7) is unrelated to the boundaries of designing variables. As established by Eq. (7), the novel AOAs exploitation and exploration stages are positioned on the optimal solution to date. The optimal solution absences diversity since the equivalent adjustment feature is used for every design variable in all iterations, as demonstrated by Eq. (7). To overwhelm this restriction, IAOA utilizes addition and subtraction operators to improve a novel location updated model for the exploitation stage.

$$x'_{i,j} = \begin{cases} b(x_j) - b(x_j) \times rand \times \overline{MOP} \times (UB_j - LB_j), \\ r_3 > 0.5 \\ b(x_j) + b(x_j) \times rand \times \overline{MOP} \times (UB_j - LB_j), \\ otherwise \end{cases} \quad (10)$$

By making variable step sizes for solution movement, Eqs. (9) and (10) improve the usage of the best solutions. Conversely, every application needs the AOA to be adjusted for four dissimilar parameters (Min, Max, α, and μ), and $b(x)$ signified the best x_j. The performance of IAOA is extraordinarily made easier by removing the terms α and μ from its expression. Fig. 2 represents the flowchart of IAOA.

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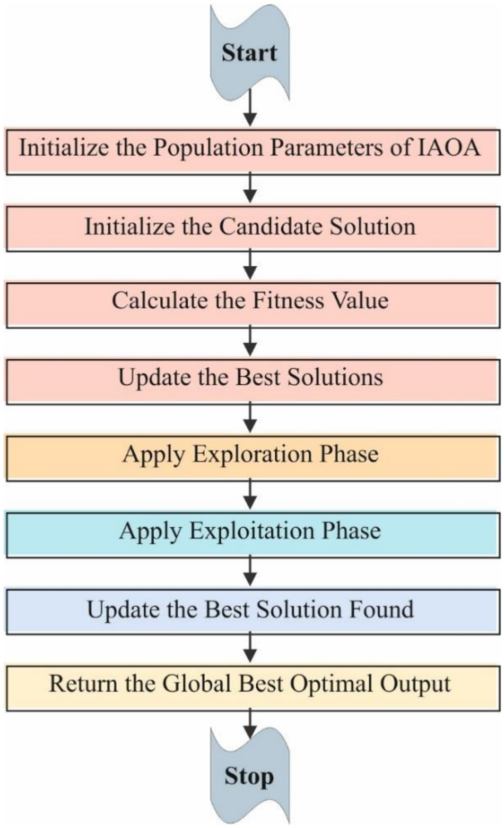

Figure 2. Flowchart of IAOA

The fitness selection is the great aspect impelling the performance of the IAOA. The hyper-parameter choice model includes the solution encoding technique to assess the efficiency of the candidate solutions. In this study, the IAOA imitates accuracy as the important standard for designing the fitness function, which was expressed as demonstrated.

$$Fitness = \max(P) \tag{11}$$

$$P = \frac{TP}{TP + FP} \tag{12}$$

Whereas, TP and FP represent the true and the false positive value.

4. Performance Validation

The performance validation of NCM-SFSMPTP model is verified under Apple Stock Price Trend and Indicators dataset [20]. This database holds 2516 samples under three targets such as bullish, bearish, and neutral as depicted in Table 1.

Table 1: Details of database

Target	No. of Samples
Bullish	951
Bearish	779
Neutral	786
Total Samples	2516

Fig. 3 illustrates the classifier solution of NCM-SFSMPTP method. Figs. 3a-3b exhibits the confusion matrices with accurate classification and identification of each class under 70%TRAPHA and 30%TESPHA. Fig. 3c demonstrates the PR analysis, demonstrating the maximal solution through each class. Eventually, Fig. 3d depicts the ROC analysis, representing capable outcomes with superior value of ROC for multiple classes.

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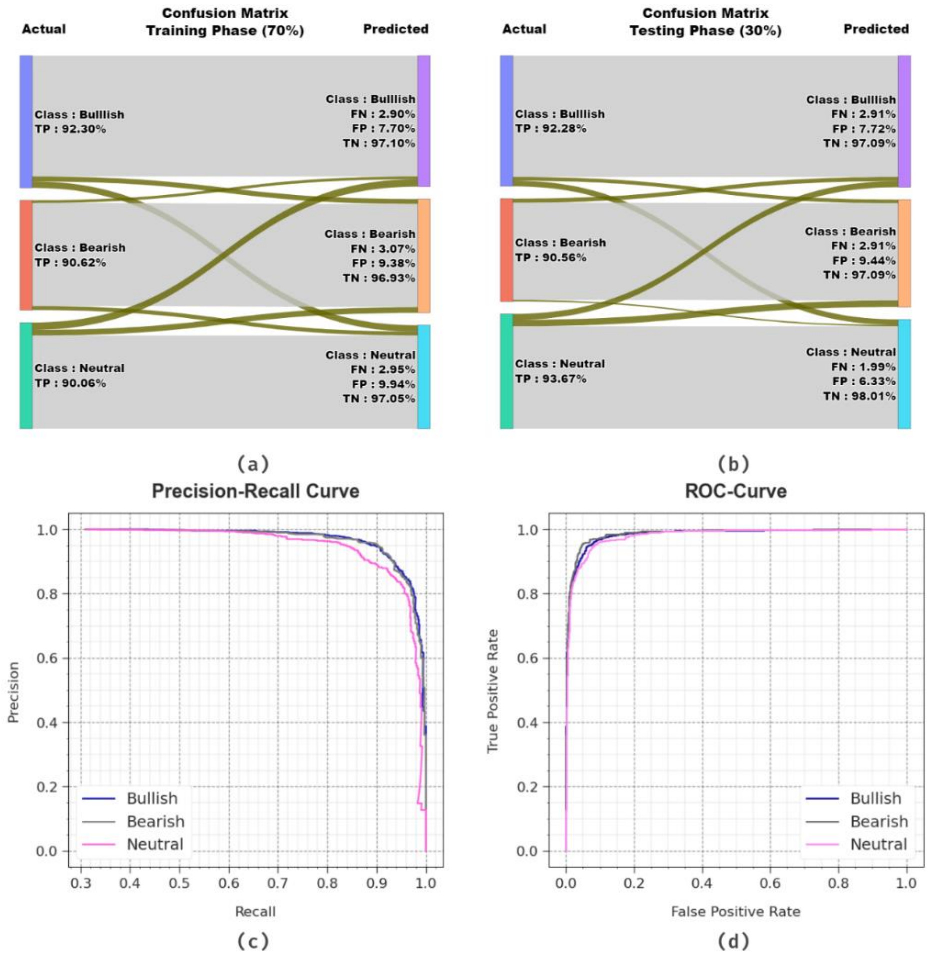

Figure 3. Classifier result of (a-b) 70% and 30% confusion matrix and (c-d) curves of PR and ROC

Table 2 investigate the stock market price tendency forecast of NCM-SFSMPTP methodology under 70%TRAPHA and 30%TESPHA. With 70%TRAPHA, the NCM-SFSMPTP model provides average $accu_y$ of 94.06%, $prec_n$ of 90.99%, $reca_l$ of 91.02%, $F1_{score}$ of 90.99%, and MCC of 86.54%. Additionally, based on 30%TESPHA, the NCM-SFSMPTP model delivers average $accu_y$ of 94.79%, $prec_n$ of 92.17%, $reca_l$ of 92.24%, $F1_{score}$ of 92.17%, and MCC of 88.28%.

Table 2: Stock market price trend prediction of NCM-SFSMPTP model under 70%TRAPHA and 30%TESPHA

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$	MCC
TRAPHA (70%)					
Bullish	93.87	92.30	91.47	91.88	86.96
Bearish	95.00	90.62	93.88	92.23	88.58
Neutral	93.30	90.06	87.71	88.87	84.09
Average	94.06	90.99	91.02	90.99	86.54
TESPHA (30%)					
Bullish	94.44	92.28	92.93	92.61	88.15
Bearish	95.50	90.56	94.62	92.54	89.36
Neutral	94.44	93.67	89.16	91.36	87.32
Average	94.79	92.17	92.24	92.17	88.28

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5. Comparative Study with Existing Works

Table 3 examines the comparative study of NCM-SFSMPTP approach with existing methodologies [21]. The consequences highlighted that the SVM, DNN, NB, RF, Recurrent-CNN, ANN and GB models have stated poor performance. While the projected NCM-SFSMPTP methodology described enhanced solution with maximum $accu_y, prec_n$, $reca_l$ and $F1_{score}$ of 94.79%, 92.17%, 92.24%, and 92.17%, respectively.

Table 3: Comparative analysis of NCM-SFSMPTP model with present models

Approaches	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$
DNN Algorithm	93.03	91.23	90.98	91.92
Random Forest	88.04	90.95	91.13	88.44
SVM Model	93.30	90.55	91.38	91.85
Naïve Bayes	91.70	89.32	88.13	88.48
Recurrent-CNN	92.78	88.37	89.26	89.70
Gradient boosting	93.01	90.03	89.12	89.87
ANN Method	92.21	88.68	88.83	88.52
NCM-SFSMPTP	94.79	92.17	92.24	92.17

6. Conclusion and Future Works

In this manuscript, a novel NCM-SFSMPTP methodology is proposed. The main goal of NCM-SFSMPTP technique relies on improving the accurate approach for stock market price trend prediction. At first, the min-max normalization methodology is used in the data normalization phase to standardize and scale data for consistency, comparability, and efficient processing. For the classification process, the NCM technique has been deployed. Eventually, the IAOA-based hyperparameter selection is implemented to enhance the classification outcomes of the NCM model. The performance validation of the NCM-SFSMPTP methodology is verified under the Apple Stock Price Trend and Indicators dataset and the outcomes are determined regarding to several measures. The experimental validation of the NCM-SFSMPTP method illustrated a superior accuracy value of 94.79% over existing models in stock market price trend prediction process. Future research can focus on developing hybrid DL models that integrate transformers and reinforcement learning for improved trend prediction. Besides, incorporating alternative data sources such as social media sentiment, economic indicators, and news analysis can enhance prediction accuracy. Finally, interpretable AI techniques can be implemented to help investors understand model predictions and build trust in AI-driven stock forecasts.

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